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Wind power forecast using wavelet neural network trained by improved Clonal selection algorithm

Hamed Chitsaz [a,*], Nima Amjady [b], Hamidreza Zareipour [a]

[a] Schulich School of Engineering, University of Calgary, Alberta, Canada
[b] Electrical Engineering Department, Semnan University, Semnan, Iran

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ABSTRACT

With the integration of wind farms into electric power grids, an accurate wind power prediction is becoming increasingly important for the operation of these power plants. In this paper, a new forecasting engine for wind power prediction is proposed. The proposed engine has the structure of Wavelet Neural Network (WNN) with the activation functions of the hidden neurons constructed based on multi-dimensional Morlet wavelets. This forecast engine is trained by a new improved Clonal selection algorithm, which optimizes the free parameters of the WNN for wind power prediction. Furthermore, Maximum Correntropy Criterion (MCC) has been utilized instead of Mean Squared Error as the error measure in training phase of the forecasting model. The proposed wind power forecaster is tested with real-world hourly data of system level wind power generation in Alberta, Canada. In order to demonstrate the efficiency of the proposed method, it is compared with several other wind power forecast techniques. The obtained results confirm the validity of the developed approach.

1. Introduction

In recent years, wind power has been the fastest growing renewable electricity generation technology in the world [1,2]. The worldwide wind capacity reached approximately 300 GW by the end of June 2013, out of which 13.9 GW were added in the first six months of 2013 [3]. In particular, Canada installed 377 MW during the first half of 2013, which is 50% more than in the previous period of 2012 [3]. In the Province of Alberta, Canada, in particular, the installed capacity reached 1087 MW in late 2012, and is expected to grow to 2388 MW by 2016 [4]. Despite the environmental benefits of wind power [5], it has an intermittent nature [6], which could affect power systems security [7] and reliability [8].

One approach to deal with wind power intermittency in operation time scale is to forecast it over an extended period of time. Accurate wind power forecasting can improve the economical and technical integration of large capacities of wind energy into the existing electricity grid [9]. Wind forecasts are important for system operators to control balancing, operation and safety of the grid [10]. On the other hand, wind power forecast errors might sometimes require system operators to re-dispatch the system in real time. The costs of re-dispatch affect electricity prices and system performance [11]. Moreover, reserve requirements are connected to wind forecast uncertainty [12]. Hence, reducing the costs of re-dispatch and contribution of spinning reserves by more accurate wind power prediction can effectively increase system operation efficiency. For instance, the economic benefits of accurate wind forecasting were assessed by GE Energy for the New York State Energy Research and Development Authority (NYSERDA) and the NYISO – all terms are defined in Appendix A. In that study, it was estimated that $125 Million, or 36%, of the cost reduction is associated with state-of-the-art wind power forecasting. It was about 80% of the estimated cost reduction that could be achieved with a perfect wind power production forecast [13].

Hence, various approaches have been proposed to improve wind power forecasting accuracy in the literature. In one group of models, wind speed and other climate variables are predicted using Numerical Weather Prediction (NWP) models, and those forecasts are used to predict the wind power output of a wind turbine or a wind farm [14,15] using turbine or farm production curves. In another group of models, the NWP forecasts, or self-generated climate variables forecasts, are fed into secondary time series models to predict wind power output for a turbine, a farm or system level wind power production. The time series models may be built based on ensemble forecasting [16], statistical approaches [17,18], or artificial intelligence techniques [19,20]. In a third group of models,

* Corresponding author. Tel.: +1 587 896 8388; fax: +1 403 282 6855.
E-mail address: hchitsaz@ucalgary.ca (H. Chitsaz).

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only past power production values are used in univariate models to predict future wind power values [21,22]. Despite improvements in wind power forecasting methods, wind power forecasts still suffer from relatively high errors, ranging from 8% to 22% (in terms of normalized Mean Squared Error) depending on several factors, such as, forecasting horizon, type of forecasting model, size of wind farm and geographic location [23].

The contribution of the present paper is to propose a new forecasting technique for short-term wind power forecasting. In particular, we develop a wind power forecasting engine based on Wavelet Neural Network (WNN) with multi-dimensional Morlet wavelets as the activation functions of the hidden neurons and Maximum Correntropy Criterion as the error measure of the training phase. We propose a stochastic search technique, which is an improved version of Clonal search algorithm, for training the forecasting engine. The significance of the proposed forecasting technique is that the combination of the WNN and the proposed training strategy is capable of capturing highly non-linear patterns in the data and result in improved forecast accuracy. Particularly, high exploitation capability of the proposed training strategy enables it to find more optimal solutions for the optimization problem of WNN training.

The remaining sections of the paper are organized as follows. A brief literature review on wind power forecasting models is provided in Section 2. The architecture of the wind forecasting model is introduced in Section 3.1. The proposed training strategy is then presented in Section 3.2. The results of the proposed wind forecasting method, obtained for the real-world test cases, are compared with the results of several other prediction approaches in Section 4. Section 5 concludes the paper.

2. Literature review

In this section, a literature review of the existing wind power forecasting models is provided. As mentioned in Section 1, the forecasting methods based on time series, either statistical models or artificial intelligence models, use historical wind power data recorded at the wind farms along with the historical data of the exogenous meteorological variables such as wind speed, temperature and humidity, providing that the data is available. Auto-Regressive Moving Average (ARMA) models [24], Auto-Regressive Integrated Moving Average (ARIMA) model [25], and Fractional ARIMA (FARIMA) model [18], have already been applied to wind speed and wind power prediction. Although time series models are simple forecasting methods and can be easily implemented, most of them are linear predictors, while wind power is generally a non-linear function of its input features.

Artificial intelligence techniques, especially Artificial Neural Networks, have been used in several papers to predict wind power generation [26]. Recurrent neural network [27], Radial Basis Function (RBF) neural network [28], and Multi-Layer Perceptron (MLP) neural networks [22], have been proposed for wind power forecasting. Although neural networks can model nonlinear input/output mapping functions, a single neural network with traditional training mechanisms has limited learning capability and may not be able to correctly learn the complex behavior of wind signal. To remedy this problem, combinations of neural networks with each other and with fuzzy inference systems such as Adaptive Neuro-Fuzzy Inference System (ANFIS) [29,30], and Hybrid Iterative Forecast Method (combining MLP neural networks) [31], have also been suggested for wind speed and power prediction. However, such models and especially fuzzy logic models, involve high complexity and a long processing time in the case of many rules [32].

Another approach to tackle the complex behavior of wind power time series is using wavelet transform. In [33], it has been discussed that wavelets can effectively be used for both stationary and non-stationary time series analysis, and that is one of the reasons for the wide and diverse applications of wavelets. Wind speed and power prediction approaches based on wavelet transform, as a preprocessor to decompose wind speed/power time series, and ANFIS [34], Auto Regressive Moving Average (ARMA) [35], Artificial Neural Network (ANN) [36], and Support Vector Regression (SVR) [37], as forecast engines, have been presented. As for SVM-based models, they highly depend on appropriately tuning of parameters and involve complex optimization process [32]. Wavelet can also be applied in a more efficient structure called wavelet neural network, in which wavelet functions are used as the activation functions of the neurons in neural networks. In [38], wavelet has been used in the form of WNN for wind speed prediction and it is trained by extended Kalman filter. Since such a model consists of many scaled and shifted wavelets of the utilized mother wavelet, it requires a powerful training algorithm to efficiently train the model and not to be trapped in local optima while finding the best input/output mapping function of the model.

In [39], a wind power prediction strategy including a Modified Hybrid Neural Network and Enhanced Particle Swarm Optimization (EPSO) has been proposed. In this paper, a developed evolutionary algorithm, i.e., EPSO, is presented to empower the training phase of the utilized neural network, which is generally a combination of three simple MLPs. Taking into consideration the advantages of wavelet transform in the form of WNN and evolutionary algorithms as the training algorithms, we propose a wind power prediction model, which is elaborated in the next section.

3. Methodology

In this section, we provide the details of the proposed forecasting engine and its training strategy. Briefly, the proposed forecasting technique is composed of a WNN structure with Morlet wavelet functions as activation functions in the hidden layer and a new training strategy. These components are described next.

3.1. The developed wavelet neural network

Wavelet transform has been used in some recent research works for wind forecasting, as a preprocessor to decompose wind speed/power time series to a set of sub-series [34,37,35,36]. The future values of the sub-series are predicted by ANFIS [34], SVR [37], ARMA [35] and ANN [36] and then combined by the inverse WT to form the forecast value of wind power/speed. Another approach to utilize wavelet in a forecast process is through constructing wavelet neural network in which a wavelet function is used as the activation function of the hidden neurons of an ANN. For instance, WNNs with Mexican hat and Morlet wavelets, shown in Fig. 1, as the activation function of the hidden neurons have been applied for another application, i.e. price forecast of electricity markets, in [40,36], respectively. Due to the local properties of wavelets and the ability of adapting the wavelet shape according to the training data set instead of adapting the parameters of the fixed shape activation function, WNNs offer higher generalization capability compared to the classical feed forward ANNs [40]. Recently, a WNN using Mexican hat mother wavelet function is proposed for wind speed forecast [38]. However, Morlet wavelet has vanishing mean oscillatory behavior with more diverse oscillations with respect to Mexican hat wavelet, which can be seen from Fig. 1, and so it can better localize high frequency components in frequency domain and various changes in time domain of severely non-smooth time series, e.g. wind power. In [41], it is mentioned